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EXAMINER	
YIP, JACK	

ART UNIT	PAPER NUMBER
3715	

NOTIFICATION DATE	DELIVERY MODE
12/05/2011	ELECTRONIC

Please find below and/or attached an Office communication concerning this application or proceeding.

The time period for reply, if any, is set in the attached communication.

Notice of the Office communication was sent electronically on above-indicated "Notification Date" to the following e-mail address(es):

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Office Action Summary	Application No.	Applicant(s)	
	10/675,232	BODNER ET AL.	
	Examiner	**Art Unit**	
	JACK YIP	3715	

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE *3* MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☒ Responsive to communication(s) filed on *8/31/2011*.

2a)☐ This action is **FINAL**. 2b)☒ This action is non-final.

3)☐ An election was made by the applicant in response to a restriction requirement set forth during the interview on _____; the restriction requirement and election have been incorporated into this action.

4)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

5)☒ Claim(s) *1-8,10-36 and 38-43* is/are pending in the application.

5a) Of the above claim(s) _____ is/are withdrawn from consideration.

6)☐ Claim(s) _____ is/are allowed.

7)☒ Claim(s) *1-8,10-36 and 38-43* is/are rejected.

8)☐ Claim(s) _____ is/are objected to.

9)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

10)☐ The specification is objected to by the Examiner.

11)☐ The drawing(s) filed on _____ is/are: a)☐ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

12)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

13)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☒ Notice of References Cited (PTO-892)

2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)

3) ☒ Information Disclosure Statement(s) (PTO/SB/08)
Paper No(s)/Mail Date *9/1/2011,5/2/2011*.

4) ☐ Interview Summary (PTO-413)
Paper No(s)/Mail Date. _____ .

5) ☐ Notice of Informal Patent Application

6) ☐ Other: _____.

DETAILED ACTION

Response to Amendment

1. In response to the amendment filed 8/31/2011; claims 1 - 8, 10 - 36, 38 - 43 are pending; claims 9, 37 are cancelled.

Claim Rejections - 35 USC § 103

2. The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

3. Claims 1 - 3, 5 - 6, 10, 28 - 29, 36, 38 - 39 are rejected under 35 U.S.C. 103(a) as being unpatentable over Donahue (US 2003/0039948 A1) in view of Best et al. (US 6,676,413 B1) and Carl Myers Kadie ("Seer: Maximum Likelihood regression for learning-speed curves", 1995; denoted as Kadie).

Re claim 1:

[Claim 1] Donahue discloses a computerized system for analyzing student performance data and providing feedback based on the student performance data (Donahue, Abstract), the system comprising: a computer network interface module configured to receive student performance data and transmit recommendation data via a computer network (Donahue, [0025], [0054]; [0032], "feedback"); a data acquisition module configured to receive the student performance data from the computer network interface module and reformat the student performance data (Donahue, [0059], [0075], "user's profile"); a performance analysis module configured to receive the reformatted student performance data from the data acquisition module and generate analysis data by analyzing the reformatted student performance data (Donahue, [0059], fig 1, "ASSESSMENT ANALYSIS"); and a real-time feedback generation module (Donahue, real-time feedback - fig. 2, 42, "INDICATE UNACCEPTABLE", 44, "INDICATE ACCEPTANCE", 50, "PRESENT LESSON RESULT", [0048], "The user logs into the system 10 at block

12. Block 12 may include prompting the user for a user identification and password to verify that the proper party is accessing the system." The user login a real time system; [0055] - [0058], i.e., [0056], "The system then repeats step at block 14, presenting the user with the next lesson element or group of lesson elements, and the process is repeated. If the user responds "no" at decision block 44, the results of the user's assessment are presented to the user as represented at block 50 (REAL-TIME FEEDBACK), and also saved and utilized by the system at block 48. The tutorial system then logs the user out of the system as at block 28."; A user is logs into the system, conduct the assessment, the system verify an assessment responses and present the result before logs out.) configured to receive the analysis data from the performance analysis module and generate the recommendation data based on the analysis data (Donahue, [0047], "feedback"), wherein the computer network interface module receives the recommendation data from the feedback generation module and transmits the recommendation data onto the computer network to a school official (Donahue, [0059] - [0062], [0075]), wherein the recommendation data comprises a plurality of courses of action (Donahue, [0026] - [0029], "A plurality of lesson elements make up a lesson or lesson plans"; i.e. [0026], "lesson may include lesson elements including (i) learning how to pronounce the sound that make … (ii) pronouncing similar sounding words... (iii) identifying the correct…") at the level of each class and school.

Donahue does not explicitly disclose a recommendation data onto the computer network to a school official at the level of each class and school. However, Best et al. (US 6,676,413 B1) teaches a system and method that analyzes student performance and provide feedback regarding the student performance, for example, to an instructor, other school official, parent or directly to the student. Best further teaches (Best, figs 5A - 5D, "Kindergarten, Benchmark One, First Grade…" figs 6A - 6B, "Class Reading Status…"; figs. 8A - 8B, col 5, lines 28 - 67; col 6, lines 1 - 37) a plurality of class, grade level and school level (Best, figs 9 - 15, fig 10, "Schools", "Campus 1", "Struggling, Emerging, On Track"…") feedback. Best further states (Best,col 4, lines 18 - 45; fig 6B, col 6, lines 7 - 56; fig 8A - 8B;) "This report aggregates the calculated predictive measures of literacy for all students in the class and presents the results in FIG. 8A as a bar chart 41 graphically depicting the number of students at each level of literacy

and as a table of numeric data 42, numerically presenting the same information as the bar chart 41. Recommendations 43 for curriculum and instruction time, as described for FIG. 6B, are also presented in this report, as shown in FIG. 8B." Best teaches the recommendation data comprises a plurality of courses of action at the level of each class and school (Best, fig 6B, fig 8B - class level; fig 13, "Attended 2 Sessions, Need support implementing reading stations, Need some support with Learning Station Rotation".). Therefore, in view of Best, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the system described in Donahue, by providing the recommendation as taught by Best, since Best states (Best, col 1, lines 63 - 67; col 2, lines 1 - 28) "Reports are given on the performance of all students tested; individual results are reported normatively; i.e., compared to other students… provided for reporting on the performance of teachers in the improvement of those reading skills. Those programs that provide general suggestions for remedial instruction activities for students do not collect information on the application of those suggestions, to allow administrators to evaluate the teachers, as well as the students…"

Donahue does not explicitly disclose "wherein the analysis data includes a learning curve and a corresponding best fit curve; and". However, Kadie teaches a system that generates empirical observations of classification-learning performance and then uses those observations to create statistical models. The models can be used to predict the number of training examples needed to achieve a desired level and the maximum accuracy possible given an unlimited number of training examples. Kadie teaches analysis data includes a learning curve (Kadie, from pgs 17 - 24, "Overview of Learning-Performance Models"; from pgs 26 - 53, "Candidate Models of Learning Performance: Design and Selection Method"; i.e., pg 18, figure 3.2: "Two statistical models"; pg 30, "Given a set of learning-performance data, the effective dimension is the d that defines a curve that best fits the data."; pg 31, "$EDit_0$ corresponds to a fixed learning curve. To allow it to be fit to data, parameters must be added."; pgs 32 - 34; pg 36; pgs 40 - 42; pg 44; pgs 47 - 48; pg 62; pg 63; pg 66; pg 70; pgs 73 - 75; pg 89) and a corresponding best fit curve (Kadie, pg 16, "fitting algorithm that efficiently find maximum-likelihood models"; pg 18, "3.1. Good-fitting models of Learning-Performance"; pg 28, "ED_{it} and $Burr_1$ are link

functions especially designed to fit learning-performance curves."; pg 31, "$EDit_0$ corresponds to a fixed learning curve. To allow it to be fit to data, parameters must be added."; pg 33, "the learning-inspired models fit and predict learning performance data better"; pg 47, "the steps to fitting a $model_{gen}$ [*z, start, skew, max*] curve to data"; pg 48, "Find the values of d and max that produce the curve that best fits the data."; pg 51, "4.4. Fitting Models to Data Efficiently"; pg 62, "fitting a curve to those points"; pg 65; pg 70; pg 76; pg 79; pg 86, "Most of the models had two parameters that needed to be fitted to the learning-performance data (*max* and *d*) and two parameters (*start* and *skew*) that could be determined from the class frequency of the classified examples."). Therefore, in view of Kadie, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the system described in Donahue, by providing the learning curve and the corresponding best fit curve as taught by Kadie, since Kadie (Kadie, pg 16) "Seer … by fitting a curve (a learning-performance model) <u>to observed learning performance data</u>. It advances the state of the art with: 1) learning-performance models that <u>embody the best constraints (for classification learning) and most useful parameters 2) fitting algorithms that efficiently find maximum-likelihood models, and 3) a demonstration, on real-world data, of a practical application</u>." Kadie further states (Kadie, pg 30) "the effective dimension of a learning problem is defined by a learning curve. Given a set of learning-performance data, the effective dimension is the *d* that defines a curve that best fits the data. Thus, unlike the way that computational learning theory uses the VC dimension, effective dimension analysis can take advantage of existing empirical performance data of an induction algorithm to make quantitative predictions of the behavior of the learning algorithm if it was given additional cases or was subjected to different environmental conditions, such as different levels of noise, irrelevant attributes, number of hidden units, etc."

<u>Re claims 2 - 3:</u>

The system of Claim 1, wherein the student performance data indicates a source of the data, wherein the data source is a school, a teacher or a student (Donahue, [0035] - [0045], [0059] -[0060]).

<u>Re claim 5;</u>

The system of Claim 1, wherein the student performance data comprises a score achieved by the student on a performance evaluation, and wherein the performance evaluation is a game, a lesson, a quiz or a test (Donahue, [0055]).

Re claim 6:

The system of Claim 1, wherein the performance data indicating a student, teacher, or school that is the source of the test data, wherein the data is encrypted (Donahue, [0048], [0060], [0067], “user logs in" a user logs in the system, therefore, the test data is encrypted.).

Re claim 10:

The system of Claim 1, wherein the computer network is the Internet (Donahue, [0025]).

Re claim 28:

The system of Claim 1, wherein data the plurality of courses of action comprises an optional course of action (Donahue, [0062]).

Re claim 29:

The system of Claim 1, wherein data the plurality of courses of action comprises a corrective course of action (Donahue, [0062]).

Re claim 36:

The system of Claim 1, wherein one of the plurality of courses of action comprises a school principal making a personnel decision for a particular class based on the analysis data (Best, fig 6B, fig 8B, see claim 1 for motivations).

Re claim 38:

The system of Claim 1, wherein one of the plurality of courses of action comprises the school official entering a command onto the computer network that enables a particular student to advance to a higher level of the game (Best, fig 4A, col 3, lines 47 - 50; "test results entry"; fig 6B, fig 8B, "games: 9 and 11; Game 10 and 1 - 8…", see claim 1 for motivations).

Re claim 39:

The system of Claim 13, wherein the plurality of courses of action include having the school official review quiz-taking skills with the student and having the student review key words or phrases (Best, figs 5A - 5B, col 4, lines 46 - 67; col 5, lines 1 - 8, "giving an example of a correct response and asking the student to respond to a practice word. The teacher is given samples of correct and incorrect responses to the practice word and scripts to use in reply to the student's response, correct or incorrect. FIG. 3B depicts a work sheet for administering a test to a single student. A series of test words 15 to be read to the student are listed, and the correct phoneme responses 16 for each test word are shown for the teacher's reference. Results of the test are entered into blanks 17 to record the student's performance on the test.") before retaking a quiz (Best, Abstract, "administering standardized oral fluency measures", see claim 1 for motivations).

4. Claims 19 - 20, 24 - 25, 40 are rejected under 35 U.S.C. 103(a) as being unpatentable over Donahue (US 2003/0039948 A1) in view of Carl Myers Kadie ("Seer: Maximum Likelihood regression for learning-speed curves", 1995; denoted as Kadie).

Re Claims 19 - 20, 24 - 25, 40:

Donahue discloses a method of analyzing successive performances by a student for a computerized quiz and providing feedback based on the performances, the method comprising: determining, via a computer system, whether a student score is above a threshold passing score to identify that the student has achieved a passing score on a quiz (Donahue, [0055]), comparing the passing score of the student to at least one score obtained from at least one subsequent quiz (Donahue, [0061]), determining, via a

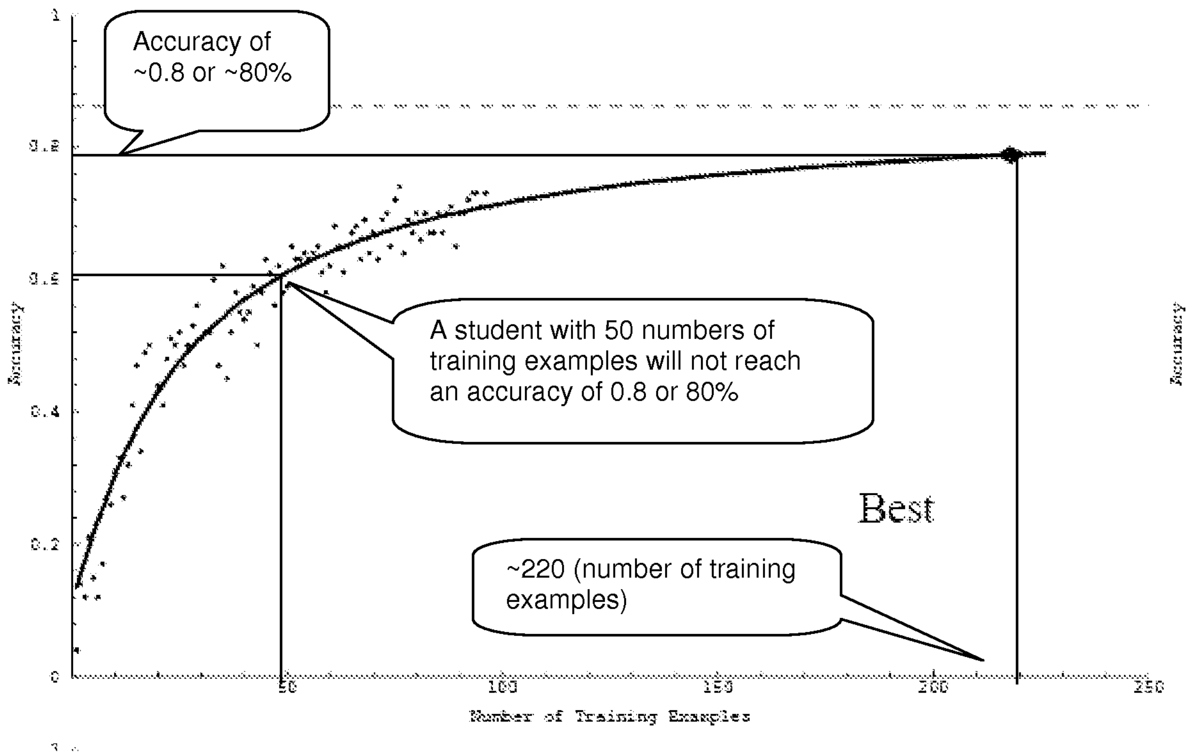
computer system, whether the student is authorized to progress to a next task of a curriculum or whether the student needs assistance from an instructor based on the comparison (Donahue, [0061] - [0062]),

Donahue additionally discloses providing feedback that a student should continue the quiz and/or be given extra attention if the student fails to pass a specific threshold after attempting a quiz a predetermined number of times (Donahue, [0057] - [0058]), wherein the method is performed by one or more computing devices (Donahue, [0009]). Donahue also discloses the invention embodied on a computer readable storage medium (as per claims 24-25; Donahue, [0010]).

Donahue does not explicitly a method comprising: generate a learning curve. However, Kadie teaches a system that generates empirical observations of classification-learning performance and then uses those observations to create statistical models. The models can be used to predict the number of training examples needed to achieve a desired level and the maximum accuracy possible given an unlimited number of training examples. Kadie further teaches a method comprising: analyzing the passing score of the student (Kadie, pgs 4 - 5, fig 1.2, "generate learning performance data"; pg 11, "analyzing learning-performance data by fitting models to the data") and the at least one subsequent quiz score to generate a learning curve (Kadie, from pgs 17 - 24, "Overview of Learning-Performance Models"; from pgs 26 - 53, "Candidate Models of Learning Performance: Design and Selection Method"; i.e., pg 18, figure 3.2: "Two statistical models"; pg 30, "Given a set of learning-performance data, the effective dimension is the d that defines a curve that best fits the data."; pg 31, "$EDit_0$ corresponds to a fixed learning curve. To allow it to be fit to data, parameters must be added."; pgs 32 - 34; pg 36; pgs 40 - 42; pg 44; pgs 47 - 48; pg 62; pg 63; pg 66; pg 70; pgs 73 - 75; pg 89) and determine whether a deviation in a learning rate exists (Kadie, pg 11, "The most popular candidate curves"; pgs 17 - 25, "Overview of Learning-Performance Models"; pg 27, "4.1. Candidate Deterministic Models"; pg 36, "d measures the learning rate"; Kadie discloses a plurality of learning models which have different learning rates (i.e., pg 40, fig 4.9; fig 68; the slope of the curves indicates the learning rates of a student); calculating a best fit curve to the learning curve (Kadie, pg 16, "fitting algorithm that efficiently find maximum-likelihood models"; pg 18, "3.1. Good-fitting models

of Learning-Performance"; pg 28, "ED_{it} and $Burr_1$ are link functions especially designed to fit learning-performance curves."; pg 31, "$EDit_0$ corresponds to a fixed learning curve. To allow it to be fit to data, parameters must be added."; pg 33, "the learning-inspired models fit and predict learning performance data better"; pg 47, "the steps to fitting a $model_{gen}$ [*z, start, skew, max*] curve to data"; pg 48, "Find the values of d and max that produce the curve that best fits the data."; pg 51, "4.4. Fitting Models to Data Efficiently"; pg 62, "fitting a curve to those points"; pg 65; pg 70; pg 76; pg 79; pg 86, "Most of the models had two parameters that needed to be fitted to the learning-performance data (*max* and *d*) and two parameters (*start* and *skew*) that could be determined from the class frequency of the classified examples."); extrapolating the best fit curve to determine (Kadie, pg 16, "fitting algorithm that efficiently find maximum-likelihood models"; pg 18, "3.1. Good-fitting models of Learning-Performance"; pg 28, "ED_{it} and $Burr_1$ are link functions especially designed to fit learning-performance curves."; pg 31, "$EDit_0$ corresponds to a fixed learning curve. To allow it to be fit to data, parameters must be added."; pg 33, "the learning-inspired models fit and predict learning performance data better"; pg 47, "the steps to fitting a $model_{gen}$ [*z, start, skew, max*] curve to data"; pg 48, "Find the values of d and max that produce the curve that best fits the data."; pg 51, "4.4. Fitting Models to Data Efficiently"; pg 62, "fitting a curve to those points"; pg 65; pg 70; pg 76; pg 79; pg 86, "Most of the models had two parameters that needed to be fitted to the learning-performance data (*max* and *d*) and two parameters (*start* and *skew*) that could be determined from the class frequency of the classified examples.") whether the threshold passing score will be reached within a maximum allotted number of times of taking the quiz (See example figure below; i.e., pg 66, figure 5.5; the maximum-likelihood models for the best trial scenario indicates that in order to reach a threshold passing score (accuracy of 0.8 or 80%); a student has to do a minimum of ~220 number of trainings; therefore if a maximum allot number of training is 50, the student will not pass the threshold score of 0.8 or 80% according to the learning curve); and generating, via the computer system, feedback data based on the determination of whether the threshold passing score will be reached within the maximum allotted number of times of taking the quiz (Kadie, from pgs 17 - 24, "Overview of Learning-Performance Models"; from pgs 26 - 53, "Candidate Models of Learning Performance: Design and Selection Method"; i.e., pg 18, figure 3.2: "Two statistical models"; pg 30, "Given a set of learning-

performance data, the effective dimension is the d that defines a curve that best fits the data."; pg 31, "$EDit_0$ corresponds to a fixed learning curve. To allow it to be fit to data, parameters must be added."; pgs 32 - 34; pg 36; pgs 40 - 42; pg 44; pgs 47 - 48; pg 62; pg 63; pg 66; pg 70; pgs 73 - 75; pg 89; the learning curve is the feedback data for determining whether the threshold passing score will be reach within the allotted number of training). [Claim 40] each quiz can have a different minimum slope (Kadie, Pg 5, fig 1.3; pg 66, fig 5.5.).



Kadie, pg 66, figure 5.5

Therefore, in view of Kadie, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the method described in Donahue, by providing the learning curve as taught by Kadie, since Kadie (Kadie, pg iii) states "The models can be used to <u>predict the number of training examples needed to achieve a desired level and the maximum accuracy</u> possible given an unlimited number of training examples." Kadie (Kadie, pgs 5 - 6) further states "How many examples like these

would the learner need to achieve 78.8% accuracy?". Kadie (Kadie, pg 16) further states "Seer … by fitting a curve (a learning-performance model) to observed learning performance data. It advances the state of the art with: 1) learning-performance models that embody the best constraints (for classification learning) and most useful parameters 2) fitting algorithms that efficiently find maximum-likelihood models, and 3) a demonstration, on real-world data, of a practical application." Kadie further states (Kadie, pg 30) "the effective dimension of a learning problem is defined by a learning curve. Given a set of learning-performance data, the effective dimension is the *d* that defines a curve that best fits the data. Thus, unlike the way that computational learning theory uses the VC dimension, effective dimension analysis can take advantage of existing empirical performance data of an induction algorithm to make quantitative predictions of the behavior of the learning algorithm if it was given additional cases or was subjected to different environmental conditions, such as different levels of noise, irrelevant attributes, number of hidden units, etc."

Applicant teaches a method which includes steps for reviewing an integrated lesson (Applicant, SPEC, [0186] - [0188], fig 30, 3050, 3074 - "Review Math Integration lesson") before retaking the quiz. Kadie teaches a method which includes steps includes a number of training examples (Kadie, pg 8, "m, the number of training examples") and testing examples (Kadie, pg 18, "k, the number of testing examples"). Kadie teaches a plurality of testing examples, but does not explicitly disclose the same testing examples (the same quiz). At the time the invention was made, it would have been an obvious matter of design choice to a person of ordinary skill in the art to retake the same quiz because applicant has not disclosed that such features provides an advantage, is used for a particular purpose, or solves a stated problem. One of ordinary skill in the art, furthermore, would have expected, both applicant's and Kadie's invention to perform equally well. One of an ordinary skill would readily recognize that retaking the same quiz would improve the test taking skills as a learner starts to memorize the answers.

5. Claims 21 - 22 and 26 - 27 are rejected under 35 U.S.C. 103(a) as being unpatentable over Donahue (US 2003/0039948 A1) in view of Carl Myers Kadie ("Seer: Maximum Likelihood

regression for learning-speed curves", 1995; denoted as Kadie), Thomas (US 6,514,084) and Mizume et al. (US 2004/0033475).

Re Claims 21 and 26:

Donahue discloses comparing quiz scores to previous quiz scores as discussed above. However, Donahue does not specifically disclose comparing the quiz scores against the number of times the quiz is taken for the more recent day. Thomas discloses comparing the quiz scores against the number of times the quiz is taken for all days the quiz is taken (Thomas, Fig. 5C). Mizuma et al. disclose that progress reports showing daily reports (Mizuma, [0066]). Therefore, in view of Mizume, it would have been obvious to one of ordinary skill in the art at the time the invention was made to analyze the scores for the most recent day, thereby providing a detailed data to analyze for a specific part of the full performance history.

Re claims 22 and 27:

Donahue discloses comparing quiz scores to previous quiz scores as discussed above. However, Donahue does not specifically disclose comparing the quiz scores against the number of times the quiz is taken for all days the quiz is taken. Thomas discloses comparing the quiz scores against the number of times the quiz is taken for all days the quiz is taken (Thomas, Fig. 5C). In view of Thomas, it would have been obvious to one of ordinary skill in the art at the time the invention was made to compare the quiz scores against the number of times the qui is taken for all days, thereby providing a complete history of data to analyze.

6. Claims 4, 11 - 12 are rejected under 35 U.S.C. 103(a) as being unpatentable over Donahue (US 2003/0039948 A1) in view of Best et al. (US 6,676,413 B1), Carl Myers Kadie ("Seer: Maximum Likelihood regression for learning-speed curves", 1995; denoted as Kadie) and Bejar et al. (US 6,526,258).

Re claim 4:

Donahue does not disclose the student performance data comprises indexing the data with codes that

have been pre-assigned to the school, teacher or student. However, Bejar teaches indexing data with codes (Bejar, fig 3, figs 8-9). Therefore, in view of Bejar, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the system described in Donahue, by providing the indexing data as taught by Bejar to provide a shorthand notation that saves time and space.

Re claims 11 - 12:

Donahue discloses analyzing stored data in a database and generating remedial recommendations based on learning problems (Donahue, [0063]). But Donahue does not specifically disclose a relational database. However, Bejar discloses the use of a relational database for analyzing responses of test questions (Bejar, Col. 2, Line 44-Col. 3, Line 17). Therefore, in view of Bejar, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the system described in Donahue, by providing the relational database as taught by Bejar to provide a detailed, organized, database from which a meaningful assessment can be made. Regarding the limitations of determining one or more universals of learning, note that the manner of operating the system does not differentiate the system from the prior art unless there results a structural difference that would patentably distinguish the systems.

7. Claims 7- 8, 13 - 18, 30 - 35 are rejected under 35 U.S.C. 103(a) as being unpatentable over Donahue (US 2003/0039948 A1) in view of Best et al. (US 6,676,413 B1), Carl Myers Kadie ("Seer: Maximum Likelihood regression for learning-speed curves", 1995; denoted as Kadie) and "Keeping Mozart in Mind" by Gordon L. Shaw (Copyright 2000) denote as Shaw.

Re claims 7 - 8:

Donahue discloses the use of data representing the progress of consecutive lessons (Donahue, [0046] - [0047]). Donahue does not specifically disclose a spatial temporal math video game. However, Shaw teaches (Shaw, pgs 22 - 28, "ROLE OF MUSIC EDUCATION IN LEARNING MATH AND SCIENCE"; pg 189, "FIRST VERSION OF S.T.A.R."; pg 275, "SPATIAL-TEMPORAL TRAINING USING S.T.A.R. TO IMPROVE MATH"; pg 275, "Matthew Peterson quickly became (and remains) the chief architect and

developer of the now proven and highly successful math video game S.T.A.R. and its evaluation program S.T.A.R.") a spatial temporal math video game. Therefore, in view of Shaw, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the system/method described in Donahue, by providing the S.T.A.R. as taught by Shaw, since Shaw (Shaw, pg 201) "The ST methods in S.T.A.R. can be extended to almost all math at all levels. As an example, the use of symmetries in ST methods has been used successfully by Xiao Leng in analyzing the behavior of equations for a pre-calculus course that she teaches at Pasadena City College. Thus, the use of spatial-temporal methods to enhance understanding of math is not limited to disadvantaged and/or very young students." (Shaw, pgs 274 - 275) "The chief goals of S.T.A.R. were to teach fractions, proportional math, and symmetry operations to 2nd grade children. These math concepts were all successfully included in S.T.A.R. in a manner that was readily understood and mastered by these children, as measured by S.T.A.R. E.P"

<u>Re claims 13 - 15, 17, 30, 33:</u>

[Claim 13] A computerized system for analyzing student performance data and providing feedback based on the student performance data (Donahue, Abstract), the system comprising: a student computer system configured to administer performance evaluation and record student response data (Donahue, [0025], [0054]; [0032], "feedback"); an education module configured to receive the student response data from the student system and generate student performance data indicative of the level of the student's mastery of the subject matter of the performance evaluation (Donahue, [0059], fig 1, "ASSESSMENT ANALYSIS"); an analysis and feedback module configured to receive the student performance data from the education module and generate feedback data by performing an analysis of the student performance data(Donahue, [0047]); and a school official computer system configured to receive the feedback data from the analysis and feedback module (Donahue, [0059] - [0062], [0075]), wherein the feedback data comprises recommendations to a school official for enhancing student performance on subsequent performance evaluations, wherein the recommendations comprise a plurality of courses of action (Donahue, [0026] - [0029], "A plurality of lesson elements make up a lesson or lesson plans"; i.e. [0026], "lesson may include lesson elements including (i) learning how to pronounce the sound that make … (ii)

pronouncing similar sounding words... (iii) identifying the correct…").

Donahue does not explicitly disclose wherein the analysis of the student performance data identifies a level of the student's mastery of the subject matter, wherein the levels are 1) mastery of the subject matter has already been obtained, 2) mastery of the subject matter is being obtained, and 3) mastery of the subject matter is not being obtained. However, Best et al. (US 6,676,413 B1) teaches a system and method that analyzes student performance and provide feedback regarding the student performance, for example, to an instructor, other school official, parent or directly to the student. Best further teaches wherein the analysis of the student performance data identifies a level of the student's mastery of the subject matter, wherein the levels are 1) mastery of the subject matter has already been obtained (Best, figs 5A - 5D, figs 6A - 6B, "ON-TRACK"; col 5, lines 43 - 67; col 6, lines 1- 26), 2) mastery of the subject matter is being obtained (Best, figs 5A - 5D, figs 6A - 6B, "EMERGING"; col 5, lines 43 - 67; col 6, lines 1-26), and 3) mastery of the subject matter is not being obtained (Best, figs 5A - 5D, figs 6A - 6B, "STRUGGLING"; col 5, lines 43 - 67; col 6, lines 1- 26). Therefore, in view of Best, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the system/method describe Donahue, by providing the three levels as taught by Best, since Best suggests (Best, col 5, lines 43 - 67; col 6, lines 1- 26, "For example, recommendations are made for Struggling readers to spend additional instruction time on a specific Struggling Reader Intervention component in the curriculum, to administer Phoneme Segmentation Fluency and Nonsense Word Fluency measures weekly, and to use specific Models and Games from the curriculum. Recommendations are made for low-scoring Emerging readers to use a specific Struggling Reader Intervention component in the curriculum and to administer Phoneme Segmentation Fluency and Nonsense Word Fluency measures monthly") different recommendation for proficiency levels.

Donahue does not explicitly disclose "wherein analysis of the student performance data comprises comparing the student performance data to a standard curve for the performance evaluation". However, Kadie teaches a system that generates empirical observations of classification-learning performance and

then uses those observations to create statistical models. The models can be used to predict the number of training examples needed to achieve a desired level and the maximum accuracy possible given an unlimited number of training examples. Kadie teaches a method for comparing (or fitting) a student performance data (Kadie, pg 11, "learning-performance data") to a plurality of standard models (or curves) (Kadie, pg 11, "The most popular candidate curves"; pgs 17 - 25, "Overview of Learning-Performance Models"; pg 27, "4.1. Candidate Deterministic Models") for selecting a good maximum-likelihood model (Kadie, pgs 26 - 53, "Candidate Models of Learning Performance: Design and Selection Method"; pg 26; "defined learning-performance models and showed how the maximum-likelihood criterion defines the best model in a possibly infinite set of candidate models. But which sets of candidate models should we consider? And how can we, algorithmically, find the best model from a set?"). Therefore, in view of Kadie, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the system described in Donahue, by comparing the learning-performance data as taught by Kadie, since Kadie (Kadie, pg 16) "Seer … by fitting a curve (a learning-performance model) to observed learning performance data. It advances the state of the art with: 1) learning-performance models that embody the best constraints (for classification learning) and most useful parameters 2) fitting algorithms that efficiently find maximum-likelihood models, and 3) a demonstration, on real-world data, of a practical application." Kadie further states (Kadie, pg 30) "the effective dimension of a learning problem is defined by a learning curve. Given a set of learning-performance data, the effective dimension is the *d* that defines a curve that best fits the data. Thus, unlike the way that computational learning theory uses the VC dimension, effective dimension analysis can take advantage of existing empirical performance data of an induction algorithm to make quantitative predictions of the behavior of the learning algorithm if it was given additional cases or was subjected to different environmental conditions, such as different levels of noise, irrelevant attributes, number of hidden units, etc."

[Claim 14] The system of Claim 13, wherein the performance evaluation is a game, a lesson, a quiz, or a test (Danohue, [0034]). [Claim 17] The system of Claim 13, wherein the student performance data comprises a score achieved by the student on a performance evaluation, and wherein the performance

evaluation is a game, a lesson, a quiz or a test (Danohue, [0034]). [Claims 13, 15, 30, 33] Donahue does not specifically disclose a spatial temporal math video game. However, Shaw teaches (Shaw, pgs 22 - 28, "ROLE OF MUSIC EDUCATION IN LEARNING MATH AND SCIENCE"; pg 189, "FIRST VERSION OF S.T.A.R."; pg 275, "SPATIAL-TEMPORAL TRAINING USING S.T.A.R. TO IMPROVE MATH"; pg 275, "Matthew Peterson quickly became (and remains) the chief architect and developer of the now proven and highly successful math video game S.T.A.R. and its evaluation program S.T.A.R.") a spatial temporal math video game. Shaw further states (Shaw, pg 189) "S.T.A.R. takes children through two stages. The first stage is a multi-level spatial-temporal training in the form of various games." Therefore, in view of Shaw, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the system/method described in Donahue, by providing the S.T.A.R. as taught by Shaw, since Shaw (Shaw, pg 201) "The ST methods in S.T.A.R. can be extended to almost all math at all levels. As an example, the use of symmetries in ST methods has been used successfully by Xiao Leng in analyzing the behavior of equations for a pre-calculus course that she teaches at Pasadena City College. Thus, the use of spatial-temporal methods to enhance understanding of math is not limited to disadvantaged and/or very young students." (Shaw, pgs 274 - 275) "The chief goals of S.T.A.R. were to teach fractions, proportional math, and symmetry operations to 2nd grade children. These math concepts were all successfully included in S.T.A.R. in a manner that was readily understood and mastered by these children, as measured by S.T.A.R. E.P"

Re claim 16:

The system of Claim 13, wherein the student performance data indicates a source of the data (Danohue, [0035] - [0045], [0059] - [0060]).

Re claim 18:

The system of Claim 13, wherein the student performance data indicating a student, teacher, or school that is the source of the test data, wherein the data is encrypted. (Donahue, [0048], [0060], [0067], "user logs in" a user logs in the system, therefore, the test data is encrypted.)

Re Claim 31:

Donahue discloses the recommendation data including an optional course of action (Danohue, [0062]).

Re Claim 32:

Donahue discloses the recommendation data including a corrective course of action (Danohue, [0062]).

Re Claims 30, 33:

Donahue discloses that actions may include remedial elements (Danohue, [0033]; see Claims 13, 15, 30, 33 above).

Re claim 34:

Donahue discloses the education module is further configured to generate student performance data after student response data received(Donahue, [0059], fig 1, “ASSESSMENT ANALYSIS”).

Re claim 35:

Donahue does not disclose a system wherein the student performance data comprises a game result. However, Shaw teaches (Shaw, pgs 22 - 28, “ROLE OF MUSIC EDUCATION IN LEARNING MATH AND SCIENCE”; pg 189, “FIRST VERSION OF S.T.A.R.”; pg 275, “SPATIAL-TEMPORAL TRAINING USING S.T.A.R. TO IMPROVE MATH”; pg 275, “Matthew Peterson quickly became (and remains) the chief architect and developer of the now proven and highly successful math video game S.T.A.R. and its evaluation program S.T.A.R.”) a spatial temporal math video game. Shaw teaches game results (Shaw, pg 27, “The results shown in Fig. 2.5 show how rapidly the 2nd grade children master the concepts in S.T.A.R.”; pg 191). Therefore, in view of Shaw, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the system/method described in Donahue, by providing the S.T.A.R. as taught by Shaw, since Shaw (Shaw, pg 201) “The ST methods in S.T.A.R. can be extended to almost all math at all levels. As an example, the use of symmetries in ST methods has been used

successfully by Xiao Leng in analyzing the behavior of equations for a pre-calculus course that she teaches at Pasadena City College. Thus, the use of spatial-temporal methods to enhance understanding of math is not limited to disadvantaged and/or very young students." (Shaw, pgs 274 - 275) "The chief goals of S.T.A.R. were to teach fractions, proportional math, and symmetry operations to 2nd grade children. These math concepts were all successfully included in S.T.A.R. in a manner that was readily understood."

12. Claim 23 is rejected under 35 U.S.C. 103(a) as being unpatentable over Tudor et al. (US 2003/0017442 A1) in view of "Keeping Mozart in Mind" by Gordon L. Shaw (Copyright 2000) denote as Shaw and Carl Myers Kadie ("Seer: Maximum Likelihood regression for learning-speed curves", 1995; denoted as Kadie).

<u>Re Claim 23:</u>

Tudor discloses a method of developing a computerized test (Tudor, [0003]; fig 2) for teaching mathematical concepts to a student (Tudor, [0036]; [0041]), the method comprising: determining a mathematical concept to be taught to a student (Tudor, [0036]; [0041]; Abstract); formulating a test of the mathematical concept (Tudor, Abstract, [0019] - [0021]; [0036]; [0041]; Abstract, "Based on the student's grade or instructional level, individually tailored tests are generated whose difficulties are geared toward the student's level of understanding in the subject."); administering, via a computer system, the test to the student (Tudor, [0037]; Abstract); testing an initially designed test of the mathematical concept (Tudor, [0021], "The test taker enters into the test at their assigned instructional level. It begins with one or two units of material to determine the starting instructional level of the test taker ..."); comparing a score on the initially designed test with a score on the test to determine whether the initially designed test score is commensurate with the test score (Tudor, [0021]; [0044] - [0049]; [0044], the initial test (current ability / instructional level) compares with subsequent test (next ability / instructional level) to determine a student should advance / decrease to the next instructional level); administering, via the computer system, a diagnostic quiz of the mathematical concept to the student (Tudor, Abstract; [0019] - [0021]; [0044] - [0049]; i.e., [0046], "The standards-based adaptive measurement adjusts the test items based on the

student's ability level."; [0048], "The subsequent learning objectives that the student receives are dependent on the answers to the previous questions. If the previous question is answered correctly, then the difficulty of the next learning objective is decreased."); comparing the test score to a score on the diagnostic quiz to determine whether the initially designed test score is commensurate with the diagnostic quiz score (Tudor, [0021]; [0044] - [0049]; [0044], the initial test (current ability / instructional level) compares with diagnostic test (next ability / instructional level)); determining that the test is deficient if the test score is not commensurate with the diagnostic quiz score (Tudor, figs 1b; fig 3; [0021]; [0044] - [0049]; [0019], "An adaptive measurement system which presents a question to the individual and, depending on whether the answer is correct or incorrect, adjusts the difficulty of the subsequent questions either up or down until the difficulty of the questions are representative of the individual's knowledge and proficiency."; the difficulty of the test / quiz can be adjust); determining adjustments to the test or the diagnostic quiz based on the comparison of the test score to the diagnostic quiz score if the initially designed test is deficient; redesigning the test based on the adjustments to the initially designed test or the diagnostic quiz (Tudor, figs 1b; fig 3; [0021]; [0044] - [0049]; [0019], "An adaptive measurement system which presents a question to the individual and, depending on whether the answer is correct or incorrect, adjusts the difficulty of the subsequent questions either up or down until the difficulty of the questions are representative of the individual's knowledge and proficiency."; the difficulty of the test / quiz can be adjusted); and integrating the redesigned test into an educational curriculum (Tudor, figs 1b; fig 3; the test/quiz are incorporated in the learning process.).

Tudor does not explicitly formulating <u>a basic spatial temporal</u> test of the mathematical concept; nor discloses an initially design <u>game</u>. However, Shaw teaches (Shaw, pgs 22 - 28, "ROLE OF MUSIC EDUCATION IN LEARNING MATH AND SCIENCE"; pg 189, "FIRST VERSION OF S.T.A.R."; pg 275, "SPATIAL-TEMPORAL TRAINING USING S.T.A.R. TO IMPROVE MATH"; pg 275, "Matthew Peterson quickly became (and remains) the chief architect and developer of the now proven and highly successful math video game S.T.A.R. and its evaluation program S.T.A.R.") a spatial temporal math video game. Shaw further states (Shaw, pg 189) "S.T.A.R. takes children through two stages. The first stage is a multi-

level spatial-temporal training in the form of various games.” Therefore, in view of Shaw, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the system/method described in Tudor, by providing the S.T.A.R. as taught by Shaw, since Shaw (Shaw, pg 201) “The ST methods in S.T.A.R. can be extended to almost all math at all levels. As an example, the use of symmetries in ST methods has been used successfully by Xiao Leng in analyzing the behavior of equations for a pre-calculus course that she teaches at Pasadena City College. Thus, the use of spatial-temporal methods to enhance understanding of math is not limited to disadvantaged and/or very young students.” (Shaw, pgs 274 - 275) “The chief goals of S.T.A.R. were to teach fractions, proportional math, and symmetry operations to 2nd grade children. These math concepts were all successfully included in S.T.A.R. in a manner that was readily understood and mastered by these children, as measured by S.T.A.R. E.P”

Tudor does not explicitly disclose a progress curve. However, Kadie teaches Tudor’s deficiency; specifically, obtain a progress curve of scores; analyzing the progress curve to determine whether it indicates successful learning and retention of the concept (Kadie teaches analysis data includes a learning curve (Kadie, from pgs 17 - 24, “Overview of Learning-Performance Models“; from pgs 26 - 53, "Candidate Models of Learning Performance: Design and Selection Method"; i.e., pg 18, figure 3.2: “Two statistical models"; pg 30, “Given a set of learning-performance data, the effective dimension is the d that defines a curve that best fits the data.”; pg 31, “EDit$_0$ corresponds to a fixed learning curve. To allow it to be fit to data, parameters must be added.”; pgs 32 - 34; pg 36; pgs 40 - 42; pg 44; pgs 47 - 48; pg 62; pg 63; pg 66; pg 70; pgs 73 - 75; pg 89). The learning / progress curve is determine whether it a subject has successfully learned and retained a concept. Therefore, in view of Kadie, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the system described in Tudor, by providing the progress curve as taught by Kadie, since Kadie (Kadie, pg 16) “Seer … by fitting a curve (a learning-performance model) to observed learning performance data. It advances the state of the art with: 1) learning-performance models that embody the best constraints (for classification learning) and most useful parameters 2) fitting algorithms that efficiently find maximum-likelihood models, and 3) a

demonstration, on real-world data, of a practical application." Kadie further states (Kadie, pg 30) "the effective dimension of a learning problem is defined by a learning curve. Given a set of learning-performance data, the effective dimension is the *d* that defines a curve that best fits the data. Thus, unlike the way that computational learning theory uses the VC dimension, effective dimension analysis can take advantage of existing empirical performance data of an induction algorithm to make quantitative predictions of the behavior of the learning algorithm if it was given additional cases or was subjected to different environmental conditions, such as different levels of noise, irrelevant attributes, number of hidden units, etc."

12. Claims 41 - 43 are rejected under 35 U.S.C. 103(a) as being unpatentable over Lai et al. (US 2004/0005536) in view of Carl Myers Kadie ("Seer: Maximum Likelihood regression for learning-speed curves", 1995; denoted as Kadie).

Re claim 41:

Lai discloses a method of analyzing successive performances by a student for a computerized quiz and providing feedback based on the performances (Lai, Abstract; "student's performance results"), the method comprising: determining, via a computer system, whether a student score is above a threshold passing score to identify that the student has achieved a passing score on a quiz (Lai, fig 8A, "System compares the student's ongoing performance results with the criteria of the next test item"; [0034]); comparing the passing score of the student to at least one score obtained from at least one subsequent quiz (Lai, fig 8A, "System compares the student's ongoing performance results with the criteria of the next test Item."; [0034]); determining, via the computer system, whether the student is authorized to progress to a next task of a curriculum or whether the student needs assistance from an instructor based on the comparison (Lai, fig 2E, "Training Plan and Summery", [0007], "identify a particular deficiency and a training recommendation module…").

[Claims 41 - 42] Lai does not explicitly disclose a learning curve. However, Kadie teaches a method comprises: analyzing the passing score of the student and the at least one subsequent quiz score to

generate a learning curve based on the scores (Kadie, from pgs 17 - 24, “Overview of Learning-Performance Models“; from pgs 26 - 53, "Candidate Models of Learning Performance: Design and Selection Method"; i.e., pg 18, figure 3.2: “Two statistical models"; pg 30, “Given a set of learning-performance data, the effective dimension is the d that defines a curve that best fits the data.”; pg 31, “$EDit_0$ corresponds to a fixed learning curve. To allow it to be fit to data, parameters must be added.”; pgs 32 - 34; pg 36; pgs 40 - 42; pg 44; pgs 47 - 48; pg 62; pg 63; pg 66; pg 70; pgs 73 - 75; pg 89) and determine whether a deviation in a learning rate exists (Kadie, pg 11, “The most popular candidate curves”; pgs 17 - 25, “Overview of Learning-Performance Models”; pg 27, “4.1. Candidate Deterministic Models"; pg 36, "d measures the learning rate"; Kadie discloses a plurality of learning models which have different learning rates (i.e., pg 40, fig 4.9; fig 68; the slope of the curves indicates the learning rates of a student); calculating a best fit curve to the learning curve (Kadie, pg 16, “fitting algorithm that efficiently find maximum-likelihood models”; pg 18, “3.1. Good-fitting models of Learning-Performance"; pg 28, “ED_{it} and $Burr_1$ are link functions especially designed to fit learning-performance curves.”; pg 31, “$EDit_0$ corresponds to a fixed learning curve. To allow it to be fit to data, parameters must be added.”; pg 33, “the learning-inspired models fit and predict learning performance data better”; pg 47, “the steps to fitting a $model_{gen}$ [*z, start, skew, max*] curve to data”; pg 48, “Find the values of d and max that produce the curve that best fits the data.”; pg 51, “4.4. Fitting Models to Data Efficiently”; pg 62, “fitting a curve to those points”; pg 65; pg 70; pg 76; pg 79; pg 86, “Most of the models had two parameters that needed to be fitted to the learning-performance data (*max* and *d*) and two parameters (*start* and *skew*) that could be determined from the class frequency of the classified examples.”); determining a slope of the best fit curve; and generating feedback data based on the determination of whether the slope of the best fit curve is greater or equal to a minimum slope for the quiz (Kadie, pg 11, “The most popular candidate curves”; pgs 17 - 25, “Overview of Learning-Performance Models”; pg 27, “4.1. Candidate Deterministic Models") for selecting a good maximum-likelihood model (Kadie, pgs 26 - 53, “Candidate Models of Learning Performance: Design and Selection Method”; pg 26; “defined learning-performance models and showed how the maximum-likelihood criterion defines the best model in a possibly infinite set of candidate models. But which sets of candidate models should we consider? And how can we, algorithmically, find

the best model from a set?"; pg 40, there are different slopes with each learning curves (fig 4.9)). [Claim 43] The method of claim 41, wherein the minimum slope for the quiz is determined by calculating the point at which the best fit curve crosses a horizontal line corresponding to a passing score (Kadie, Pg 5, fig 1.3; pg 66, fig 5.5.). Therefore, in view of Kadie, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the method described in Lai, by providing the learning curve as taught by Kadie, since Kadie (Kadie, pg iii) states "The models can be used to predict the number of training examples needed to achieve a desired level and the maximum accuracy possible given an unlimited number of training examples." Kadie (Kadie, pgs 5 - 6) further states "How many examples like these would the learner need to achieve 78.8% accuracy?". Kadie (Kadie, pg 16) further states "Seer … by fitting a curve (a learning-performance model) to observed learning performance data. It advances the state of the art with: 1) learning-performance models that embody the best constraints (for classification learning) and most useful parameters 2) fitting algorithms that efficiently find maximum-likelihood models, and 3) a demonstration, on real-world data, of a practical application." Kadie further states (Kadie, pg 30) "the effective dimension of a learning problem is defined by a learning curve. Given a set of learning-performance data, the effective dimension is the *d* that defines a curve that best fits the data. Thus, unlike the way that computational learning theory uses the VC dimension, effective dimension analysis can take advantage of existing empirical performance data of an induction algorithm to make quantitative predictions of the behavior of the learning algorithm if it was given additional cases or was subjected to different environmental conditions, such as different levels of noise, irrelevant attributes, number of hidden units, etc."

[Claim 42] Lai does not disclose a method comprising: comparing the learning curve of the student to a standard curve for the quiz, wherein each particular quiz has a corresponding standard curve; and generating feedback data regarding the stage of learning for the student based on the comparison. However, Kadie teaches a system that generates empirical observations of classification-learning performance and then uses those observations to create statistical models. The models can be used to predict the number of training examples needed to achieve a desired level and the maximum accuracy

possible given an unlimited number of training examples. Kadie teaches a method for comparing (or fitting) a student performance data (Kadie, pg 11, “learning-performance data") to a plurality of standard models (or curves) (Kadie, pg 11, “The most popular candidate curves”; pgs 17 - 25, “Overview of Learning-Performance Models”; pg 27, “4.1. Candidate Deterministic Models") for selecting a good maximum-likelihood model (Kadie, pgs 26 - 53, “Candidate Models of Learning Performance: Design and Selection Method”; pg 26; “defined learning-performance models and showed how the maximum-likelihood criterion defines the best model in a possibly infinite set of candidate models. But which sets of candidate models should we consider? And how can we, algorithmically, find the best model from a set?”). Therefore, in view of Kadie, it would have been obvious to one of ordinary skill in the art, at the time of invention, to modify the system described in Lai, by comparing the learning-performance data as taught by Kadie, since Kadie (Kadie, pg 16) “Seer … by fitting a curve (a learning-performance model) to observed learning performance data. It advances the state of the art with: 1) learning-performance models that embody the best constraints (for classification learning) and most useful parameters 2) fitting algorithms that efficiently find maximum-likelihood models, and 3) a demonstration, on real-world data, of a practical application.” Kadie further states (Kadie, pg 30) “the effective dimension of a learning problem is defined by a learning curve. Given a set of learning-performance data, the effective dimension is the *d* that defines a curve that best fits the data. Thus, unlike the way that computational learning theory uses the VC dimension, effective dimension analysis can take advantage of existing empirical performance data of an induction algorithm to make quantitative predictions of the behavior of the learning algorithm if it was given additional cases or was subjected to different environmental conditions, such as different levels of noise, irrelevant attributes, number of hidden units, etc.”

Response to Arguments

8. Applicant’s arguments, see pgs 12 - 19, filed 8/31/2011, with respect to the rejection(s) of claim(s) 1 - 8, 10 - 36, 38 - 41 under 35 U.S.C.§ 103(a) have been fully considered and are persuasive. Therefore, the rejection has been withdrawn. However, upon further consideration, a new ground(s) of

rejection is made in view of Carl Myers Kadie (“Seer: Maximum Likelihood regression for learning-speed curves”, 1995; denoted as Kadie).

Conclusion

9. The prior art made of record and not relied upon is considered pertinent to applicant's disclosure.

“THE LEARNING CURVE: HISTORICAL REVIEW AND COMPREHENSIVE SURVEY" by Louis E. Yelle”

“The Stochastic Learning Curve: Optimal Production in the Presence of Learning-Curve Uncertainty" By Joseph B. Mazzola and Kevin F. McCardleReviewed

“Rigorous Learning Curve Bounds from Statistical Mechanics" by DAVID HAUSSLER, MICHAEL KEARNS, H. SEBASTIAN SEUNG, NAFTALI TISHBY

“Toward a Theory of Continuous Improvement and the Learning Curve” by Willard I. Zangwill and Paul B. Kantor

Any inquiry concerning this communication or earlier communications from the examiner should be directed to JACK YIP whose telephone number is (571)270-5048. The examiner can normally be reached on Monday - Friday 9:30am - 5:00pm EST.

If attempts to reach the examiner by telephone are unsuccessful, the examiner’s supervisor, Xuan Thai can be reached on (571)272-7147. The fax phone number for the organization where this application or proceeding is assigned is 571-273-8300.

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Examiner, Art Unit 3715

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